In [2]:
```
import pandas as pd
import numpy as np;
import datetime as dt
import matplotlib.pyplot as plt
%matplotlib inline
```

In [3]:
```
# reading the data/ csv file
df = pd.read_csv("complaint.csv")
```

In [4]:
```
df.head()
```

Out[4]:

	Ticket #	Customer Complaint	Date	Date_month_year	Time	Received Via	City	State	Zip code
0	250635	Cable Internet Speeds	22-04-2015	22-Apr-15	3:53:50 PM	Customer Care Call	Abingdon	Maryland	21009
1	223441	Payment disappear - service got disconnected	04-08-2015	04-Aug-15	10:22:56 AM	Internet	Acworth	Georgia	30102
2	242732	Speed and Service	18-04-2015	18-Apr-15	9:55:47 AM	Internet	Acworth	Georgia	30101
3	277946	Imposed a New Usage Cap of 300GB that punishe...	05-07-2015	05-Jul-15	11:59:35 AM	Internet	Acworth	Georgia	30101
4	307175	not working and no service to boot	26-05-2015	26-May-15	1:25:26 PM	Internet	Acworth	Georgia	30101

In [5]:

```
# making the month column in the dataframe
df['month'] = pd.DatetimeIndex(df['Date_month_year']).month
```

In [6]:

```
# to check
df.head(10)
```

Out[6]:

	Ticket #	Customer Complaint	Date	Date_month_year	Time	Received Via	City	State	Zip code
0	250635	Cable Internet Speeds	22-04-2015	22-Apr-15	3:53:50 PM	Customer Care Call	Abingdon	Maryland	21009
1	223441	Payment disappear - service got disconnected	04-08-2015	04-Aug-15	10:22:56 AM	Internet	Acworth	Georgia	30102
2	242732	Speed and Service	18-04-2015	18-Apr-15	9:55:47 AM	Internet	Acworth	Georgia	30101
3	277946	Imposed a New Usage Cap of 300GB that punishe...	05-07-2015	05-Jul-15	11:59:35 AM	Internet	Acworth	Georgia	30101
4	307175	not working and no service to boot	26-05-2015	26-May-15	1:25:26 PM	Internet	Acworth	Georgia	30101
5	338519	ISP Charging for arbitrary data limits with ov...	06-12-2015	06-Dec-15	9:59:40 PM	Internet	Acworth	Georgia	30101
6	361148	Throttling service and unreasonable data caps	24-06-2015	24-Jun-15	10:13:55 AM	Customer Care Call	Acworth	Georgia	30101

	Ticket #	Customer Complaint	Date	Date_month_year	Time	Received Via	City	State	Zip code
7	359792	refuses to help troubleshoot and correct my s...	23-06-2015	23-Jun-15	6:56:14 PM	Internet	Adrian	Michigan	49221
8	318072	extended outages	06-01-2015	06-Jan-15	11:46:30 PM	Customer Care Call	Alameda	California	94502
9	371214	Raising Prices and Not Being Available To Ask...	28-06-2015	28-Jun-15	6:46:31 PM	Customer Care Call	Alameda	California	94501

In [7]:

```
#to count the frequency of complaints in different months
df["month"].value_counts()
```

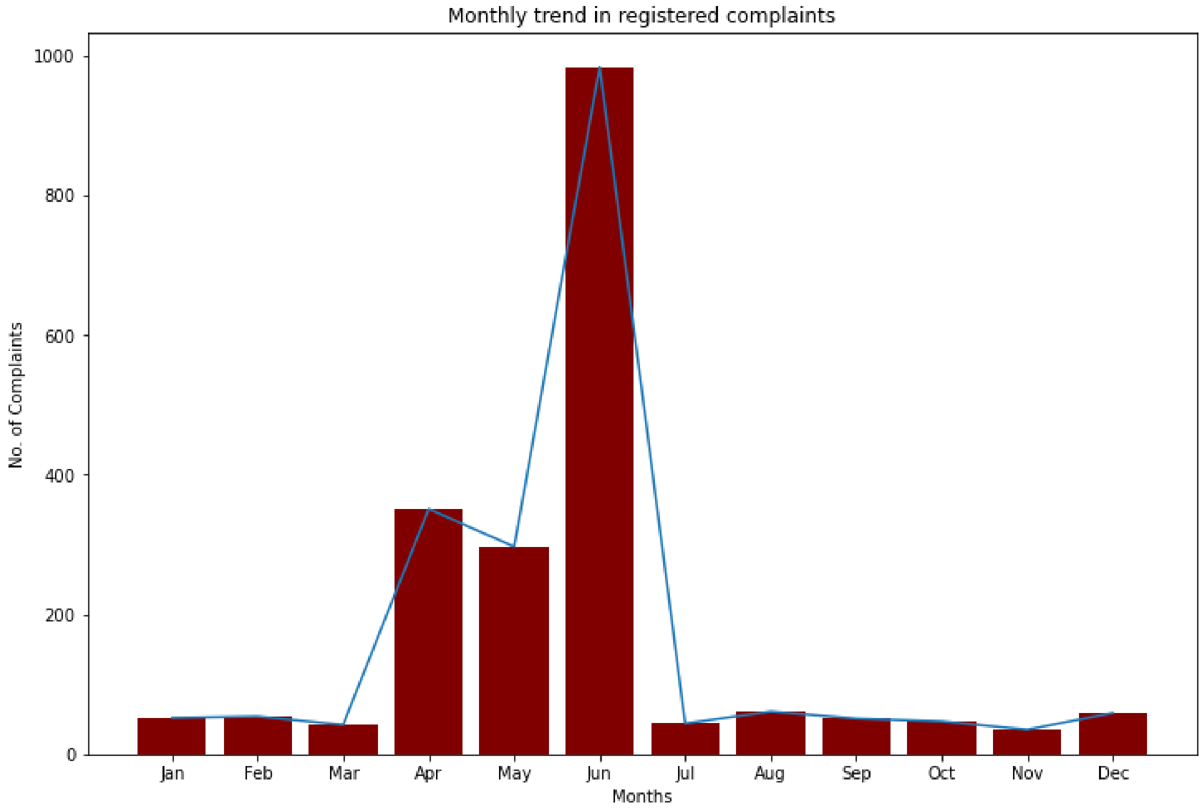
Out[7]:

```
6     984
4     351
5     297
8      61
12     59
2      54
1      52
9      51
10     47
7      44
3      42
11     35
Name: month, dtype: int64
```

1. Produce the trend chart about the monthly registered complaints

In [9]:

```
X = ['Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov','Dec']
Y = [52,54,42,351,297,984,44,61,51,47,35,59]
fig = plt.figure(figsize = (12, 8))

# creating the bar plot
plt.bar(X, Y, color ='maroon',
        width = 0.8)
# creating the trend in the same graph.
plt.plot(X,Y)

plt.xlabel("Months")
plt.ylabel("No. of Complaints")
plt.title("Monthly trend in registered complaints")
plt.show()
```



2. Generate a tabular output with frequencies of complaints

In [10]:
```
# library to get the frequency of different words in the data
import nltk
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
```

In [11]:
```
# collecting all the data as a single string
data = ""
for i in df["Customer Complaint"]:
    data = data + i + " "
```

In [12]:
```
# printing some data to get better undersatnding
print(data[:100])
```

```
 Cable Internet Speeds Payment disappear - service got disconnected Spe
ed and Service  Imposed a New
```

In [13]:
```
#tokenizing the words
tokens = word_tokenize(data)
```

In [12]:
```
# removing stopwords and non alpha numeric words
tokens_without_sw = [word for word in tokens if not word in stopwords.words() and word.isalnum()]
```

In [13]:
```
# making all the words as small
tokens_without_sw = [word.lower() for word in tokens_without_sw]
```

In [14]:
```
len(tokens_without_sw)
```

Out[14]:
```
6682
```

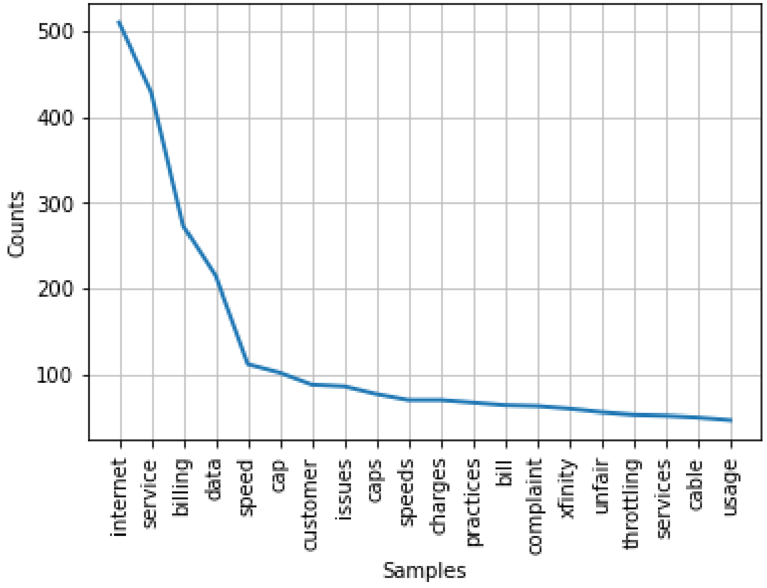
In [15]:
```
# calculating the frequency of each appearing word
freq=nltk.FreqDist(tokens_without_sw)
```

In [16]:
```
freq
```

Out[16]:
```
FreqDist({'internet': 510, 'service': 429, 'billing': 273, 'data': 215,
'speed': 112, 'cap': 102, 'customer': 88, 'issues': 86, 'caps': 77, 'sp
eeds': 70, ...})
```

3. Find which complaint types are maximum i.e., internet, network issues, etc

In [17]:
```
# plotting top 20 frequent words in the data
freq.plot(20)
```



Out[17]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f20b6e9c50>
```

In the above plot we can see that the maximum complaints are related to internet issues, then comes the issues related to services, then billing and so on.

4. Provide the state wise status of complaint in the form of stacked bar

In [18]:
```
# no. of different states
df["State"].nunique()
```

Out[18]:
```
42
```

In [19]:
```
# and their names
df["State"].unique()
```

Out[19]:
```
array(['Maryland', 'Georgia', 'Michigan', 'California', 'New Mexico',
       'Indiana', 'Virginia', 'Illinois', 'Pennsylvania', 'Oregon',
       'Massachusetts', 'New Hampshire', 'Minnesota', 'Tennessee',
       'Florida', 'Alabama', 'Washington', 'Colorado', 'Texas',
       'New York', 'New Jersey', 'Maine', 'West Virginia', 'Montana',
       'Mississippi', 'Connecticut', 'Vermont', 'Kentucky',
       'South Carolina', 'Ohio', 'Utah', 'Delaware', 'Missouri',
       'Arkansas', 'Nevada', 'Louisiana', 'Kansas', 'Arizona',
       'North Carolina', 'District Of Columbia', 'District of Columbi
a',
       'Iowa'], dtype=object)
```

assumption : Here I'm taking the closed and solved complaints to be Resolved and rest tags in the category of unresolved complaints.

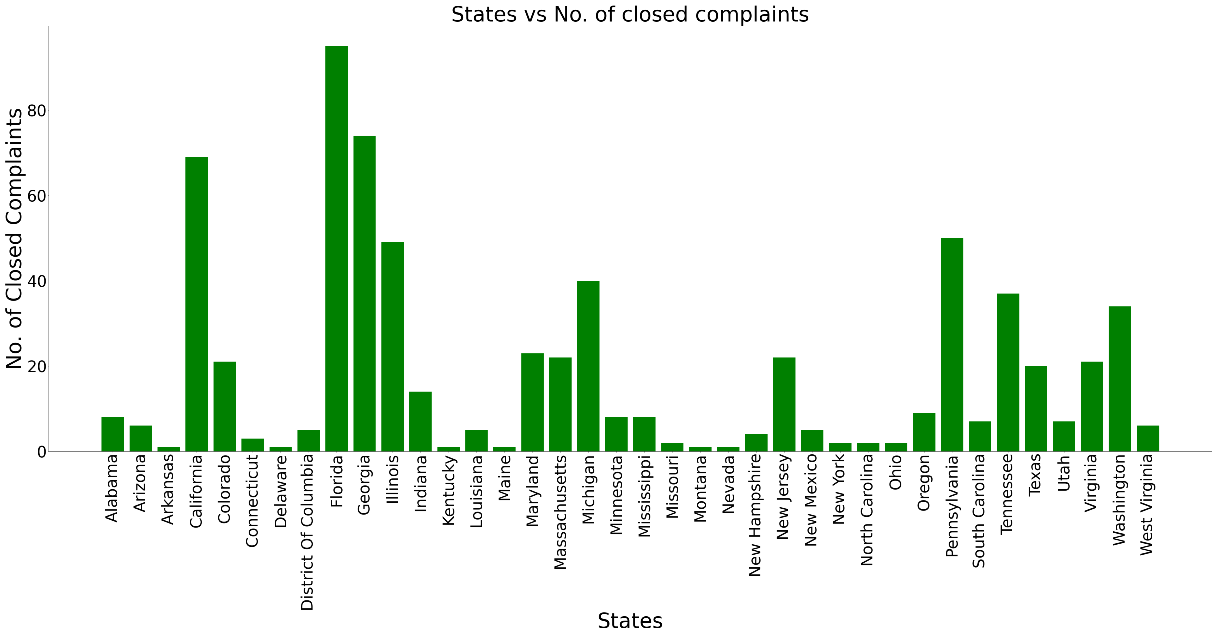
In [16]:
```
# lists that will contain the corresponding status complaints
closed = []
country_closed = []
Open = []
```

```
country_open = []
solved = []
country_solved = []
pending = []
country_pending = []
# dictionary to store resolved and unresolved complaints.
res = {}
unres = {}
total = {}
for i in df["State"]:
    res[i] = 0
    unres[i] = 0
    total[i] = 0
cnt = 0
# iterating over the data by grouping the state and status.
for i, g in df.groupby(['State','Status']):
    if(i[1] == "Closed"):
        closed.append(len(g))
        res[i[0]] += len(g)
        total[i[0]] += len(g)
        country_closed.append(i[0])
    if(i[1] == "Open"):
        Open.append(len(g))
        unres[i[0]] += len(g)
        total[i[0]] += len(g)
        country_open.append(i[0])
    if(i[1] == "Solved"):
        solved.append(len(g))
        res[i[0]] += len(g)
        total[i[0]] += len(g)
        country_solved.append(i[0])
    if(i[1] == "Pending"):
        pending.append(len(g))
        unres[i[0]] += len(g)
        total[i[0]] += len(g)
        country_pending.append(i[0])
```

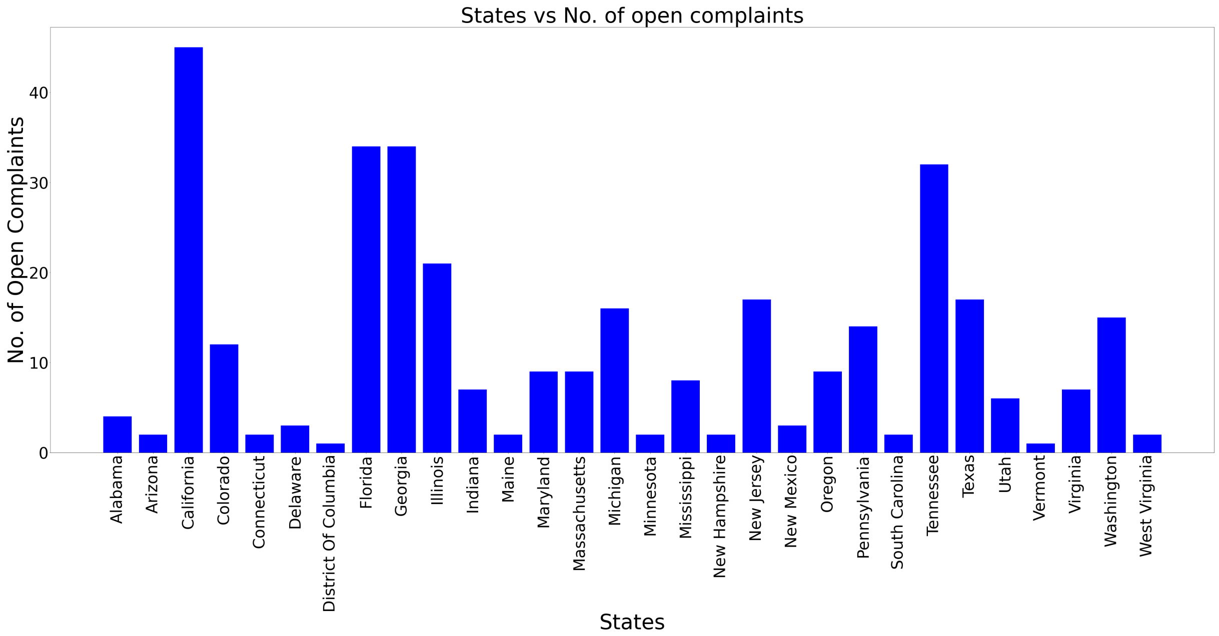
In [19]:

```
fig = plt.figure(figsize = (80, 30))
```

```
# creating the bar plot
plt.bar(country_closed, closed, color ='green',
        width = 0.8)
plt.yticks(fontsize = 60)
plt.xticks(rotation = 90,fontsize = 60)
plt.xlabel("States",fontsize = 80)
plt.ylabel("No. of Closed Complaints",fontsize = 80)
plt.title("States vs No. of closed complaints",fontsize = 80)
plt.show()
```

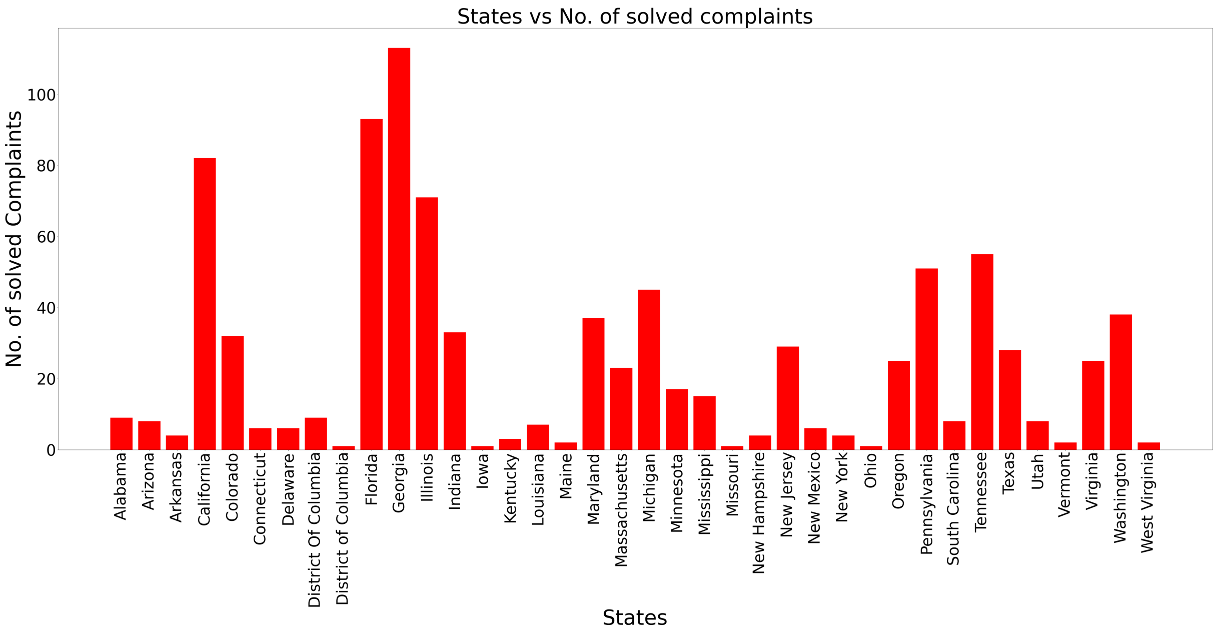


In [22]:
```
fig = plt.figure(figsize = (80, 30))

# creating the bar plot
plt.bar(country_open, Open, color ='blue',
        width = 0.8)
plt.yticks(fontsize = 60)
plt.xticks(rotation = 90,fontsize = 60)
plt.xlabel("States",fontsize = 80)
plt.ylabel("No. of Open Complaints",fontsize = 80)
plt.title("States vs No. of open complaints",fontsize = 80)
plt.show()
```



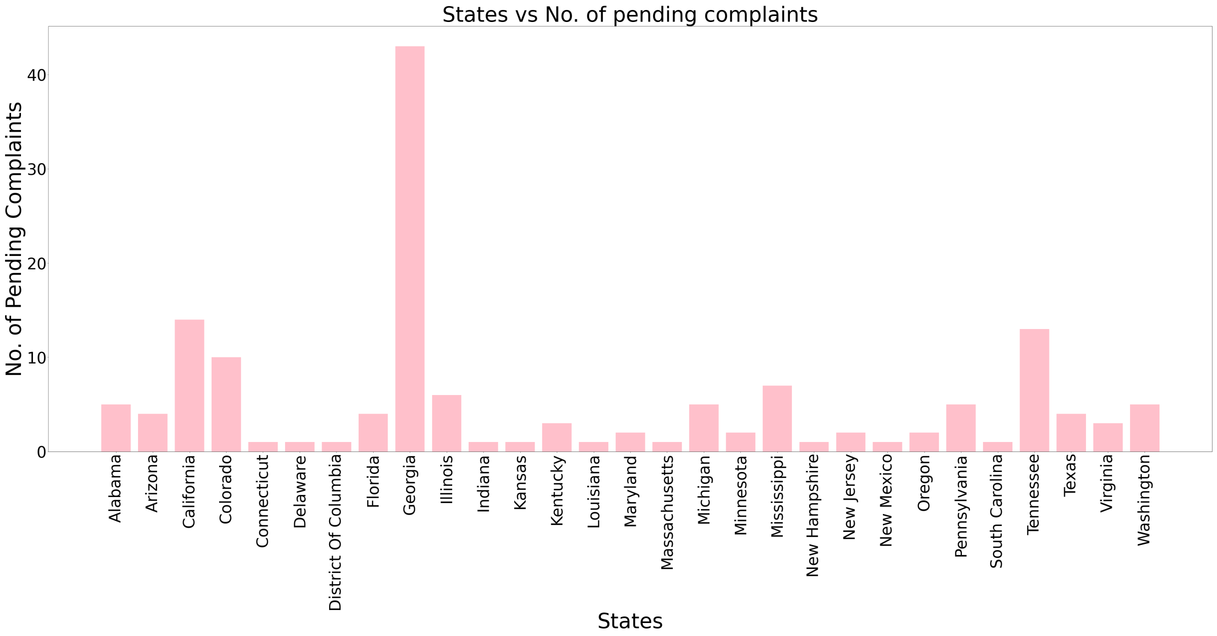
In [24]:

```
fig = plt.figure(figsize = (80, 30))

# creating the bar plot
plt.bar(country_solved, solved, color ='red',
        width = 0.8)
plt.yticks(fontsize = 60)
plt.xticks(rotation = 90,fontsize = 60)
plt.xlabel("States",fontsize = 80)
plt.ylabel("No. of solved Complaints",fontsize = 80)
plt.title("States vs No. of solved complaints",fontsize = 80)
plt.show()
```



In [25]:

```
fig = plt.figure(figsize = (80, 30))

# creating the bar plot
plt.bar(country_pending, pending, color ='pink',
        width = 0.8)
plt.yticks(fontsize = 60)
plt.xticks(rotation = 90,fontsize = 60)
plt.xlabel("States",fontsize = 80)
plt.ylabel("No. of Pending Complaints",fontsize = 80)
plt.title("States vs No. of pending complaints",fontsize = 80)
plt.show()
```



5. Report which state has registered maximum and minimum complaint

In [26]:

```
# no of complaints in different states
df["State"].value_counts()
```

Out[26]:

```
Georgia                 264
Florida                 226
California              210
Illinois                147
Tennessee               137
Pennsylvania            120
Michigan                106
Washington               92
Colorado                 75
Maryland                 71
New Jersey               70
Texas                    69
```

```
Virginia                   56
Massachusetts              55
Indiana                    55
Oregon                     45
Mississippi                38
Minnesota                  29
Alabama                    26
Utah                       21
Arizona                    20
South Carolina             18
District Of Columbia       16
New Mexico                 15
Louisiana                  13
Connecticut                12
New Hampshire              11
Delaware                   11
West Virginia              10
Kentucky                    7
New York                    6
Arkansas                    5
Maine                       5
Ohio                        3
Missouri                    3
Vermont                     3
North Carolina              2
Montana                     1
District of Columbia        1
Nevada                      1
Kansas                      1
Iowa                        1
Name: State, dtype: int64
```

From the above table, it is easily observed that maximum complaints are registered in "GEORGIA" and minimum complaints (i.e only 1) is registered in "Kansas","District of Columbia", "Iowa", "Nevada", "Montana".

6. Which state has the highest and lowest percentage of unresolved complaints

In [27]:

```
# printing the dictionary having keys as countries and values as resolv
ed complaints.
print(res)
```

```
{'Maryland': 60, 'Georgia': 187, 'Michigan': 85, 'California': 151, 'Ne
w Mexico': 11, 'Indiana': 47, 'Virginia': 46, 'Illinois': 120, 'Pennsyl
vania': 101, 'Oregon': 34, 'Massachusetts': 45, 'New Hampshire': 8, 'Mi
nnesota': 25, 'Tennessee': 92, 'Florida': 188, 'Alabama': 17, 'Washingt
on': 72, 'Colorado': 53, 'Texas': 48, 'New York': 6, 'New Jersey': 51,
'Maine': 3, 'West Virginia': 8, 'Montana': 1, 'Mississippi': 23, 'Conne
cticut': 9, 'Vermont': 2, 'Kentucky': 4, 'South Carolina': 15, 'Ohio':
3, 'Utah': 15, 'Delaware': 7, 'Missouri': 3, 'Arkansas': 5, 'Nevada':
1, 'Louisiana': 12, 'Kansas': 0, 'Arizona': 14, 'North Carolina': 2, 'D
istrict Of Columbia': 14, 'District of Columbia': 1, 'Iowa': 1}
```

In [28]:

```
# printing the dictionary having keys as countries and values as unreso
lved complaints.
print(unres)
```

```
{'Maryland': 11, 'Georgia': 77, 'Michigan': 21, 'California': 59, 'New
Mexico': 4, 'Indiana': 8, 'Virginia': 10, 'Illinois': 27, 'Pennsylvani
a': 19, 'Oregon': 11, 'Massachusetts': 10, 'New Hampshire': 3, 'Minneso
ta': 4, 'Tennessee': 45, 'Florida': 38, 'Alabama': 9, 'Washington': 20,
'Colorado': 22, 'Texas': 21, 'New York': 0, 'New Jersey': 19, 'Maine':
2, 'West Virginia': 2, 'Montana': 0, 'Mississippi': 15, 'Connecticut':
3, 'Vermont': 1, 'Kentucky': 3, 'South Carolina': 3, 'Ohio': 0, 'Utah':
6, 'Delaware': 4, 'Missouri': 0, 'Arkansas': 0, 'Nevada': 0, 'Louisian
a': 1, 'Kansas': 1, 'Arizona': 6, 'North Carolina': 0, 'District Of Col
umbia': 2, 'District of Columbia': 0, 'Iowa': 0}
```

In [29]:

```
# printing the dictionary having keys as countries and values as total
 complaints.
print(total)
```

```
{'Maryland': 71, 'Georgia': 264, 'Michigan': 106, 'California': 210, 'N
ew Mexico': 15, 'Indiana': 55, 'Virginia': 56, 'Illinois': 147, 'Pennsy
ew Mexico': 15, 'Indiana': 55, 'Virginia': 56, 'Illinois': 147, 'Pennsy
lvania': 120, 'Oregon': 45, 'Massachusetts': 55, 'New Hampshire': 11,
'Minnesota': 29, 'Tennessee': 137, 'Florida': 226, 'Alabama': 26, 'Wash
ington': 92, 'Colorado': 75, 'Texas': 69, 'New York': 6, 'New Jersey':
70, 'Maine': 5, 'West Virginia': 10, 'Montana': 1, 'Mississippi': 38,
'Connecticut': 12, 'Vermont': 3, 'Kentucky': 7, 'South Carolina': 18,
'Ohio': 3, 'Utah': 21, 'Delaware': 11, 'Missouri': 3, 'Arkansas': 5, 'N
evada': 1, 'Louisiana': 13, 'Kansas': 1, 'Arizona': 20, 'North Carolin
a': 2, 'District Of Columbia': 16, 'District of Columbia': 1, 'Iowa':
1}
```

In [30]:

```
# finding resolved and unresolved complaints percentage
res_percentage = {}
unres_percentage = {}
for i in df["State"]:
    res_percentage[i] = 0
    unres_percentage[i] = 0
for j in res.items():
    res_percentage[j[0]] = (res[j[0]]/total[j[0]])*100
for k in unres.items():
    unres_percentage[k[0]] = (unres[k[0]]/total[k[0]])*100
```

In [31]:

```
# printing the dictionary having keys as countries and values as % of r
esolved complaints.
print(res_percentage)
```

```
{'Maryland': 84.50704225352112, 'Georgia': 70.83333333333334, 'Michiga
n': 80.18867924528303, 'California': 71.9047619047619, 'New Mexico': 7
3.33333333333333, 'Indiana': 85.45454545454545, 'Virginia': 82.14285714
285714, 'Illinois': 81.63265306122449, 'Pennsylvania': 84.1666666666666
7, 'Oregon': 75.55555555555556, 'Massachusetts': 81.81818181818183, 'Ne
w Hampshire': 72.72727272727273, 'Minnesota': 86.20689655172413, 'Tenne
ssee': 67.15328467153284, 'Florida': 83.1858407079646, 'Alabama': 65.38
461538461539, 'Washington': 78.26086956521739, 'Colorado': 70.666666666
66667, 'Texas': 69.56521739130434, 'New York': 100.0, 'New Jersey': 72.
85714285714285, 'Maine': 60.0, 'West Virginia': 80.0, 'Montana': 100.0,
'Mississippi': 60.526315789473685, 'Connecticut': 75.0, 'Vermont': 66.6
6666666666666, 'Kentucky': 57.14285714285714, 'South Carolina': 83.3333
3333333334, 'Ohio': 100.0, 'Utah': 71.42857142857143, 'Delaware': 63.63
636363636363, 'Missouri': 100.0, 'Arkansas': 100.0, 'Nevada': 100.0, 'L
636363636363, 'Missouri': 100.0, 'Arkansas': 100.0, 'Nevada': 100.0, 'L
ouisiana': 92.3076923076923, 'Kansas': 0.0, 'Arizona': 70.0, 'North Car
olina': 100.0, 'District Of Columbia': 87.5, 'District of Columbia': 10
0.0, 'Iowa': 100.0}
```

In [32]:

```
# printing the dictionary having keys as countries and values as % of u
nresolved complaints.
print(unres_percentage)
```

```
{'Maryland': 15.492957746478872, 'Georgia': 29.166666666666668, 'Michig
an': 19.81132075471698, 'California': 28.095238095238095, 'New Mexico':
26.666666666666668, 'Indiana': 14.545454545454545, 'Virginia': 17.85714
2857142858, 'Illinois': 18.367346938775512, 'Pennsylvania': 15.83333333
3333332, 'Oregon': 24.444444444444443, 'Massachusetts': 18.181818181818
183, 'New Hampshire': 27.27272727272727, 'Minnesota': 13.79310344827586
1, 'Tennessee': 32.846715328467155, 'Florida': 16.8141592920354, 'Alaba
ma': 34.61538461538461, 'Washington': 21.73913043478261, 'Colorado': 2
9.333333333333332, 'Texas': 30.434782608695656, 'New York': 0.0, 'New J
ersey': 27.142857142857142, 'Maine': 40.0, 'West Virginia': 20.0, 'Mont
ana': 0.0, 'Mississippi': 39.473684210526315, 'Connecticut': 25.0, 'Ver
mont': 33.33333333333333, 'Kentucky': 42.857142857142854, 'South Caroli
na': 16.666666666666664, 'Ohio': 0.0, 'Utah': 28.57142857142857, 'Delaw
are': 36.36363636363637, 'Missouri': 0.0, 'Arkansas': 0.0, 'Nevada': 0.
0, 'Louisiana': 7.6923076923076925, 'Kansas': 100.0, 'Arizona': 30.0,
'North Carolina': 0.0, 'District Of Columbia': 12.5, 'District of Colum
bia': 0.0, 'Iowa': 0.0}
```

countries having highest percentage of unresolved complaints:

1. Kansas (100%)

2. Tennessee (32.84%)

countries having lowest percentage of unresolved complaints:

1. Iowa

2. **DOC**

3. **Nevada**

4. **Arkansas**

5. **Missouri**

6. **Ohio**

7. **Montana**

8. **New York**

9. **North Carolina**

Note : all these countries have 0% of unresolved complaints.

THANK YOU

Question 2

In [35]:

```
# reading the second dataset
df_mart = pd.read_csv('Mart.csv')
```

In [36]:

```
df_mart.head()
```

Out[36]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
0	1	05-02-2010	1643690.90	0	42.31	2.572	211.096358	8.106
1	1	12-02-2010	1641957.44	1	38.51	2.548	211.242170	8.106
2	1	19-02-2010	1611968.17	0	39.93	2.514	211.289143	8.106
3	1	26-02-2010	1409727.59	0	46.63	2.561	211.319643	8.106
4	1	05-03-2010	1554806.68	0	46.50	2.625	211.350143	8.106

In [37]:

```
# to check if there is any null values in the data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2077 entries, 0 to 2076
Data columns (total 12 columns):
 #   Column                       Non-Null Count  Dtype 
---  ------                       --------------  ----- 
 0   Ticket #                     2077 non-null   object
 1   Customer Complaint           2077 non-null   object
 2   Date                         2077 non-null   object
 3   Date_month_year              2077 non-null   object
 4   Time                         2077 non-null   object
 5   Received Via                 2077 non-null   object
 6   City                         2077 non-null   object
 7   State                        2077 non-null   object
 8   Zip code                     2077 non-null   int64 
 9   Status                       2077 non-null   object
 10  Filing on Behalf of Someone  2077 non-null   object
 11  month                        2077 non-null   int64 
```

```
dtypes: int64(2), object(10)
memory usage: 194.8+ KB
```

1. Which store has maximum sales

In [38]:

```
s = df_mart[df_mart["Store"] == 1]["Weekly_Sales"].sum()
```

In [40]:

```
# calculating the sales of different stores
sales = {}
for i in range(1,46):
    sales[i] = df_mart[df_mart["Store"] == i]["Weekly_Sales"].sum()
```

In [42]:

```
# printing the total sales of different stores
sales
```

Out[42]:

```
{1: 222402808.85,
 2: 275382440.97999996,
 3: 57586735.06999999,
 4: 299543953.38,
 5: 45475688.900000006,
 6: 223756130.64000002,
 7: 81598275.14,
 8: 129951181.12999998,
 9: 77789218.99000001,
 10: 271617713.89,
 11: 193962786.8,
 12: 144287230.15,
 13: 286517703.8,
 14: 288999911.34000003,
 15: 89133683.92,
 16: 74252425.39999999,
 17: 127782138.83000003,
 18: 155114734.21000004,
 19: 206634862.09999996,
 20: 301397792.46000004,
 21: 108117878.91999999,
 22: 147075648.57,
 23: 198750617.85000002,
 24: 194016021.28000003,
 25: 101061179.16999999,
 26: 143416393.79,
 27: 253855916.88,
 28: 189263680.57999998,
 29: 77141554.30999999,
 30: 62716885.120000005,
 31: 199613905.5,
 32: 166819246.16000003,
 33: 37160221.95999999,
 34: 138249763.0,
 35: 131520672.08,
 36: 53412214.97,
 37: 74202740.32,
 38: 55159626.42,
 39: 207445542.46999997,
 40: 137870309.79,
 41: 181341934.89,
 42: 79565752.42999999,
 43: 90565435.41,
 44: 43293087.84,
 45: 112395341.42000002}
```

In [43]:

```
# finding the store having maximun sales
mx = 0
store = 0
for k in sales.items():
    if(k[1] > mx):
        mx = k[1]
        store = k[0]
print(store)
```

```
20
```

so store 20 has maximum sales

2. Which store has maximum standard deviation i.e., the sales vary a lot. Also, find out the coefficient of mean to standard deviation (coefficient of variation)

In [45]:

```
# total number of stores
df_mart["Store"].nunique()
```

Out[45]:

```
45
```

In [46]:

```
# calculating the coefficient of variation and store having maximum and minimum standard deviation
mx_std_dev = 0;
mn_std_dev = 1000000000;
mx_store = 0
mn_store = 0
coeff = 0
print("The Coefficient of variations for stores are as follows :")
for i in range(1,46):
    std = df_mart[df_mart["Store"] == i].std()[1]
    mean = df_mart[df_mart["Store"] == i].mean()[1]
    if(std > mx_std_dev):
        mx_std_dev = std
        mx_store = i
    if(std < mn_std_dev):
        mn_std_dev = std
        mn_store = i
    coeff = (std/mean) *100
    print(i,coeff)
print("The store having maximum standard deviation is :",mx_store,"With standard deviation",mx_std_dev)
print("The store having minimum standard deviation is :",mn_store,"With standard deviation",mn_std_dev)
```

```
The Coefficient of variations for stores are as follows :
1 10.02921226813075
2 12.34238763319183
3 11.502140735338804
4 12.708253937002839
5 11.866844091939742
```

```
5 11.866844091939742
6 13.582285902663829
7 19.730468653665728
8 11.695283213906869
9 12.689546764678369
10 15.913349066639102
11 12.22618336004468
12 13.792532199977735
13 13.251362792719142
14 15.713673600948338
15 19.33839877822955
16 16.51806549478143
17 12.552067141232682
18 16.28454974226666
19 13.26801153482639
20 13.090268561738489
21 17.029239217349453
22 15.678287578148591
23 17.9721149197535
24 12.363737661375541
25 15.98604024072346
26 11.011066299216315
27 13.515544496695316
28 13.73297416512492
29 18.374246746816343
30 5.2008038555445175
31 9.016105262945947
32 11.831049176166283
33 9.286835290692942
34 10.82252383219858
35 22.968111389976414
36 16.25789124577327
37 4.208411895180792
38 11.087544692154392
39 14.990779108026006
40 12.342978096269446
41 14.817711243560769
42 9.03353280932982
43 6.4103629270192375

44 8.179331054568062
```

```
44 8.179331054568062
45 16.561272979512935
The store having maximum standard deviation is : 14 With standard devia
tion 317569.9494755083
The store having minimum standard deviation is : 37 With standard devia
tion 21837.4611900489
```

The store having maximum standard deviation is : 14 With standard deviation 317569.9494755083

The store having minimum standard deviation is : 37 With standard deviation 21837.4611900489

3. Some holidays have a negative impact on sales. Find out holidays which have higher sales than the mean sales in non-holiday season for all stores together

In [48]:

```python
# mean sales of non holiday season for all stores together
mean_non_holiday = df_mart[df_mart["Holiday_Flag"] == 0].mean()[1]
```

In [49]:

```python
# the mean of sales in non holiday season
mean_non_holiday
```

Out[49]:

```
1041256.3802088555
```

In [51]:

```python
# calculating the sales of different holiday seasons which have sales m
ore than the mean sales of non holiday season
l = ["12-02-2010","11-02-2011","10-02-2012","10-09-2010","09-09-2011",
"07-09-2012","26-11-2010","31-12-2010","30-12-2011"]
for i in l:
    sales_holiday_stores = df_mart[df_mart["Date"] == i]["Weekly_Sales"
].mean()
    if(sales_holiday_stores > mean_non_holiday):
        print("holiday Season : ",i,"||","Sales : ",sales_holiday_store
s)
```

```
holiday Season :  12-02-2010 || Sales :  1074148.3917777783
holiday Season :  11-02-2011 || Sales :  1051915.3953333334
holiday Season :  10-02-2012 || Sales :  1111320.176
holiday Season :  07-09-2012 || Sales :  1074001.318
holiday Season :  26-11-2010 || Sales :  1462688.960888889
```

4. Provide a monthly and 6 month view of sales in units and give insights

In [75]:

```
# adding month and year column
df_mart['Month'] = df_mart["Date"].apply(lambda x : x.split('-')[1])
df_mart['Year'] = df_mart["Date"].apply(lambda x : x.split('-')[2])
```

In [78]:

```
df_mart.head()
```

Out[78]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
0	1	05-02-2010	1643690.90	0	42.31	2.572	211.096358	8.106
1	1	12-02-2010	1641957.44	1	38.51	2.548	211.242170	8.106
2	1	19-02-2010	1611968.17	0	39.93	2.514	211.289143	8.106
3	1	26-02-2010	1409727.59	0	46.63	2.561	211.319643	8.106
4	1	05-03-2010	1554806.68	0	46.50	2.625	211.350143	8.106

In [79]:
```
# making year list
year_list = df_mart["Year"].unique().tolist()
```

In [80]:
```
year_list
```

Out[80]:
```
['2010', '2011', '2012']
```

In [81]:
```
# making monthly list
month_list = df_mart["Month"].unique().tolist()
```

In [82]:
```
month_list
```

Out[82]:
```
['02', '03', '04', '05', '06', '07', '08', '09', '10', '11', '12', '0
1']
```

In [83]:
```
# calculating the monthly sales
monthly_sales = {}
for i in year_list:
    for j in month_list:
        monthly_sales[j+"-"+i] = df_mart[(df_mart["Month"] == j) & (df_
mart["Year"] == i)]["Weekly_Sales"].sum()
```

tabular data for monthly sales

In [84]:
```
# printing the month vs it's corresponding sales.
monthly_sales
```

Out[84]:
```
{'02-2010': 190332983.04000002,
 '03-2010': 181919802.5,
 '04-2010': 231412368.05,
 '05-2010': 186710934.34000003,
 '06-2010': 192246172.36,
 '07-2010': 232580125.98,
 '08-2010': 187640110.89,
 '09-2010': 177267896.37,
 '10-2010': 217161824.02,
 '11-2010': 202853370.14,
 '12-2010': 288760532.72,
 '01-2010': 0.0,
 '02-2011': 186331327.87,
 '03-2011': 179356448.29000002,
 '04-2011': 226526510.97,
 '05-2011': 181648158.16,
 '06-2011': 189773385.19,
 '07-2011': 229911398.87,
 '08-2011': 188599332.25,
 '09-2011': 220847738.42000002,
 '10-2011': 183261283.14999998,
 '11-2011': 210162354.87,
 '12-2011': 288078102.48,
 '01-2011': 163703966.82999998,
 '02-2012': 192063579.54000002,
 '03-2012': 231509650.49,
 '04-2012': 188920905.95,
 '05-2012': 188766479.45,
 '06-2012': 240610329.28999996,
 '07-2012': 187509452.39999998,
 '08-2012': 236850765.68,
 '09-2012': 180645544.47,
 '10-2012': 184361680.42000002,
 '11-2012': 0.0,
 '12-2012': 0.0,
 '01-2012': 168894471.66}
```

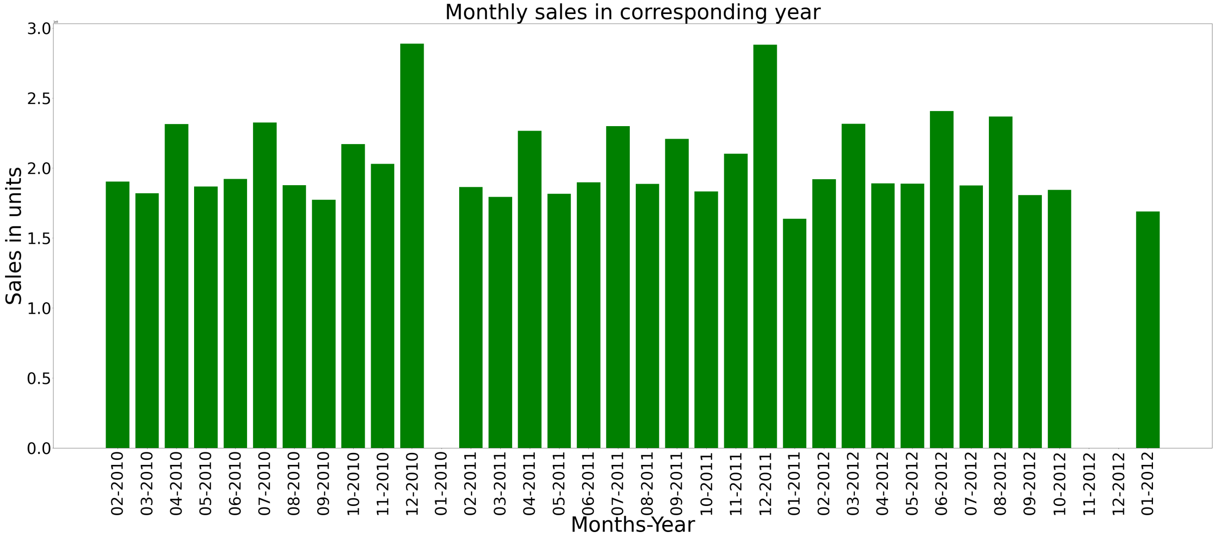
In [114]:

```
X = []
Y = []
for i in monthly_sales.items():
    X.append(i[0])
    Y.append(i[1])
```

In [116]:

```
fig = plt.figure(figsize = (80, 30))

# creating the bar plot
```

```
plt.bar(X, Y, color ='green',
        width = 0.8)
plt.yticks(fontsize = 60)
plt.xticks(rotation = 90,fontsize = 60)
plt.xlabel("Months-Year",fontsize = 80)
plt.ylabel("Sales in units",fontsize = 80)
plt.title("Monthly sales in corresponding year",fontsize = 80)
plt.show()
```



Insight : the maximum sales in both year 2010 and 2011 are found in the month of december..may be because these are the closing dates and stores provide the maximum sales in these months. Moreover due to christmas and new year people purchase more goods.

In [85]:
```
# calculating half yearly sales. Due to the data constraints the last v
alue if from August 2012 to October 2012 only i.e 3 months
half_yearly_sales = {}
half_yearly_sales["Feb-2010 to July-2010"] = monthly_sales["02-2010"]+m
onthly_sales["03-2010"]+monthly_sales["04-2010"]+monthly_sales["05-201
0"]+monthly_sales["06-2010"]+monthly_sales["07-2010"]
half_yearly_sales["Aug-2010 to Jan-2011"] = monthly_sales["08-2010"]+mo
```

```
nthly_sales["09-2010"]+monthly_sales["10-2010"]+monthly_sales["11-2010"
]+monthly_sales["12-2010"]+monthly_sales["01-2011"]
half_yearly_sales["Feb-2011 to July-2011"] = monthly_sales["02-2011"]+m
onthly_sales["03-2011"]+monthly_sales["04-2011"]+monthly_sales["05-201
1"]+monthly_sales["06-2011"]+monthly_sales["07-2011"]
half_yearly_sales["Aug-2011 to jan-2012"] = monthly_sales["08-2011"]+mo
nthly_sales["09-2011"]+monthly_sales["10-2011"]+monthly_sales["11-2011"
]+monthly_sales["12-2011"]+monthly_sales["01-2012"]
half_yearly_sales["Feb-2012 to July-2012"] = monthly_sales["02-2012"]+m
onthly_sales["03-2012"]+monthly_sales["04-2012"]+monthly_sales["05-201
2"]+monthly_sales["06-2012"]+monthly_sales["07-2012"]
half_yearly_sales["Aug-2012 to Oct-2012"] = monthly_sales["08-2012"]+mo
nthly_sales["09-2012"]+monthly_sales["10-2012"]
```

In [86]:

```
# half yearly sales
half_yearly_sales
```

Out[86]:

```
{'Feb-2010 to July-2010': 1215202386.27,
 'Aug-2010 to Jan-2011': 1237387700.97,
 'Feb-2011 to July-2011': 1193547229.35,
 'Aug-2011 to jan-2012': 1259843282.8300002,
 'Feb-2012 to July-2012': 1229380397.12,
 'Aug-2012 to Oct-2012': 601857990.5699999}
```

Statistical Model

For store 2 develop Linear Regression model– Utilize variables like date and restructure dates as 1 for 5 Feb 2010 (starting from the earliest date in order). Hypothesize if CPI, unemployment, and fuel price have any impact on sales.

In [88]:

```
# making the dataframe that contains entries of store 2 only
store2 = df_mart[df_mart["Store"] == 2]
```

In [89]:
```
store2.head()
```

Out[89]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployme
143	2	05-02-2010	2136989.46	0	40.19	2.572	210.752605	8.32
144	2	12-02-2010	2137809.50	1	38.49	2.548	210.897994	8.32
145	2	19-02-2010	2124451.54	0	39.69	2.514	210.945160	8.32
146	2	26-02-2010	1865097.27	0	46.10	2.561	210.975957	8.32
147	2	05-03-2010	1991013.13	0	47.17	2.625	211.006754	8.32

In [90]:
```
# importing the required libraries
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

In [91]:
```
# reshape using numpy.
y = store2["Weekly_Sales"].values.reshape(-1,1)
```

In [92]:
```
print(y)
```

```
[[2136989.46]
 [2137809.5 ]
 [2124451.54]
 [1865097.27]
 [1991013.13]
 [1990483.78]
 [1946070.88]
 [1750197.81]
 [2066187.72]
 [1954689.21]
 [1874957.94]
 [1821990.93]
 [1802450.29]
 [2042581.71]
 [1880752.36]
 [1896937.1 ]
 [1957113.89]
 [2102539.93]
 [2025538.76]
 [2001636.96]
 [1939927.09]
 [2003940.64]
 [1880902.62]
 [1845879.79]
 [1781717.71]
 [1804246.16]
 [1991909.98]
 [1895601.05]
 [1964335.23]
 [1863840.49]
 [1904608.09]
 [1839128.83]
 [1793903.6 ]
 [1724557.22]
 [1827440.43]
 [1849921.44]
 [1794355.49]
 [1737947.64]
 [1802755.11]
 [1939061.41]
 [1916812.74]
 [1956739.17]
 [2658725.29]
 [2015781.27]
 [2378726.55]
 [2609166.75]
```

```
[3436007.68]
[1750434.55]
[1758050.79]
[1744193.58]
[1751384.9 ]
[1695371.68]
[1929346.23]
[2168041.61]
[2080884.82]
[1833511.08]
[1981607.78]
[1879107.31]
[1902557.66]
[1766162.05]
[1800171.36]
[1847552.61]
[1856467.84]
[1886339.6 ]
[1745545.28]
[1837743.6 ]
[1838513.07]
[1688281.86]
[1797732.56]
[1933756.21]
[1929153.16]
[1953771.99]
[1790925.8 ]
[1866243.  ]
[1853161.99]
[1785187.29]
[1743816.41]
[1680693.06]
[1876704.26]
[1812768.26]
[1844094.59]
[1821139.91]
[1809119.7 ]
[1748000.65]
[1691439.52]
```

```
 [1669299.78]
 [1650394.44]
 [1837553.43]
 [1743882.19]
 [1834680.25]
 [1769296.25]
 [1959707.9 ]
 [1920725.15]
 [1902762.5 ]
 [2614202.3 ]
 [1954952.  ]
 [2290549.32]
 [2432736.52]
 [3224369.8 ]
 [1874226.52]
 [1799520.14]
 [1744725.48]
 [1711769.11]
 [1660906.14]
 [1935299.94]
 [2103322.68]
 [2196688.46]
 [1861802.7 ]
 [1952555.66]
 [1937628.26]
 [1976082.13]
 [1790439.16]
 [1857480.84]
 [2129035.91]
 [1935869.1 ]
 [1847344.45]
 [1764133.09]
 [1923957.09]
 [1917520.99]
 [2000940.67]
 [1912791.09]
 [1910092.37]
 [2010216.49]
 [1962924.3 ]
 [1887733.21]
 [1881046.12]
 [2041507.4 ]
 [1830075.13]
 [1819666.46]
 [1757923.88]
 [1946104.64]
 [1866719.96]
 [1928016.01]
 [1876788.15]
 [1947083.3 ]
 [1898777.07]
 [1814806.63]
 [1829415.67]
 [1746470.56]
 [1998321.04]
 [1900745.13]
 [1847990.41]
 [1834458.35]]
```

In [93]:

```
# features
X = store2.iloc[:,3:8].values
```

In [99]:

```
# making the object of class implementing Linear Regression
model = LinearRegression()
```

In [100]:

```
# splitting the dataset into 80-20 format
XTrain,XTest,YTrain,YTest = train_test_split(X,y,test_size = 0.2,random
_state = 0)
```

In [101]:

```
print(XTrain.shape)
print(YTrain.shape)
```

```
(114, 5)
(114, 1)
```

In [102]:

```
# training (i.e fitting the line)
```

```
model.fit(XTrain,YTrain)
```

Out[102]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normaliz
e=False)
```

In [103]:

```
# prediction over the unseen testing data
y_prediction = model.predict(XTest)
print(y_prediction)
```

```
[[1946426.32066277]
 [1879951.40417502]
 [1882260.89155458]
 [1909126.59112045]
 [1892200.14285578]
 [1997585.75845128]
 [1927578.52051966]
 [1813000.5457226 ]
 [1833659.49252555]
 [1999323.51369375]
 [2071612.75963028]
 [1896266.45746001]
 [1928436.96804825]
 [2092813.80122205]
 [1818429.20917997]
 [1925316.57926143]
 [1871939.28466764]
 [1904079.49057578]
 [1901651.0150834 ]
 [1896505.41482992]
 [1811046.25035841]
 [1953992.22854554]
 [1881372.17767078]
 [1902070.30684743]
 [1818201.52222804]
 [1930985.06653398]
 [1824031.3024909 ]
 [1969032.74561768]
 [1961000.05765377]]
```

In [104]:

```
# coefficients of different features in the hypothesis
print(model.coef_)
```

```
[[  58401.325891     -2238.23488176 -257714.5342688    54515.96326202
   281398.25517897]]
```

In [106]:

```
# intercept of the best fit line
print(model.intercept_)
```

```
[-11011203.59366687]
```

The coefficients that are positive signifies that, as the value of the feature corresponding to this coefficient increases the value of dependent variable increases (i.e. sales in this case and vice versa.

Similarly high value of the coefficient means the feature corresponding to this coefficient is more related to the dependent variable(i.e. sales in this case) and vice versa.

Therefore Holiday flag have positive coefficient with value 58401.325

Therefore Temperature have negative coefficient with value 2238.234

Therefore Fuel Price have negative coefficient with value 257714.534

Therefore CPI have positive coefficient with value 54515.963

Therefore Unemployment have positive coefficient with value 281398.255

THANK YOU

In [ ]: